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Kalman Filtering for Sensor Fusion in a Human Tracking System

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1. Introduction

Robotic systems need to be context-aware in order to adapt their tasks to the different states of their environment. This context-awareness does not only imply the detection of the objects which are near the robot but it also includes the tracking of people who collaborate with it. Thus, human-robot interaction tasks become more natural and unobtrusive because robots are able to change their behaviour depending on this context information.

In industrial environments, these context-aware systems should also guarantee the safety of human operators who interact with industrial robots. Therefore, a precise localization of all the limbs of the body of the operator has to be determined. In this chapter, the use of an inertial motion capture system for tracking full-body movements of the operator is described. It is composed of 18 IMUs (Inertial Measurement Units) attached to the body of the operator which determine the rotation angle of each joint. It has several advantages over other motion capture technologies: easy installation, self-containment, occlusions-free and precise rotational measurements. However, it accumulates a small error (drift) in the estimation of the global translation of the human operator in the environment which becomes considerable after several movements of the operator. Therefore, an additional location system based on UWB (Ultra-Wide Band) signals has been added to correct this drift accumulation.

The features of both tracking systems are complementary. The inertial motion capture system registers accurate joint rotation angles at a high rate while the UWB location system estimates global translation in the environment at a low rate. The combination of these systems will reduce the drawbacks of each one with the advantages of the other one. On one hand, the global translation measurements of the UWB system will correct the accumulated drift of the motion capture system. On the other hand, the high rate measurements of the motion capture system will complete the periods of time when there are not any measurements from the UWB system.

Firstly, a simple fusion algorithm of both tracking systems is presented. This first fusion algorithm transforms measurements from the two systems in the same coordinate system by recalculating the transformation matrix each time a new measurement from the UWB system is received. This approach relies heavily on the accuracy of the measurements from the UWB system because the transformation matrix recalculation assumes that the last UWB measurement is completely correct. Thus, errors in UWB measurements are not considered and only the translational errors of the motion capture system are corrected. Furthermore,

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when there is a considerable distance between the last measurement from the motion capture system and the last measurement from the UWB system, significant gaps appear in the final trajectory returned by the fusion algorithm. Another fusion algorithm which takes into account UWB errors has been developed in order to overcome these drawbacks and obtain more continuous trajectories. This second fusion algorithm is based on a Kalman filter.

This chapter is organized as follows. First of all, the two tracking systems are described in detail in section 2. In section 3, the fusion algorithms developed to combine the measurements of these systems are explained and compared with previous research. In section 4, several experiments are presented in order to compare the accuracy of both fusion algorithms. The Kalman filter algorithm is applied in a human-robot interaction task. Finally, the conclusions of this chapter and future research are presented in section 5.

2. Overview of the tracking systems

2.1 Inertial motion capture system

A system based on inertial sensors has been selected because it has several advantages over other motion capture sensor technologies (Welch & Foxlin, 2002). It is comfortable for the user because it does not limit his/her movements like mechanical motion capture systems. Its measurements are not negatively influenced by magnetic distortions like magnetic systems. Finally, it does not suffer from occlusion problems like optical systems.

The inertial motion capture system used in the present research (Animazoo, 2008) is composed of 18 small IMUs (Inertial Measurement Units) attached to a lycra suit (Fig. 1a) which is worn by a human operator. Each IMU (Fig. 1b) estimates the orientation (roll, pitch and yaw) of the operator's limb to which it is attached by combining the measurements from three miniaturized gyroscopes, three accelerometers and three magnetometers

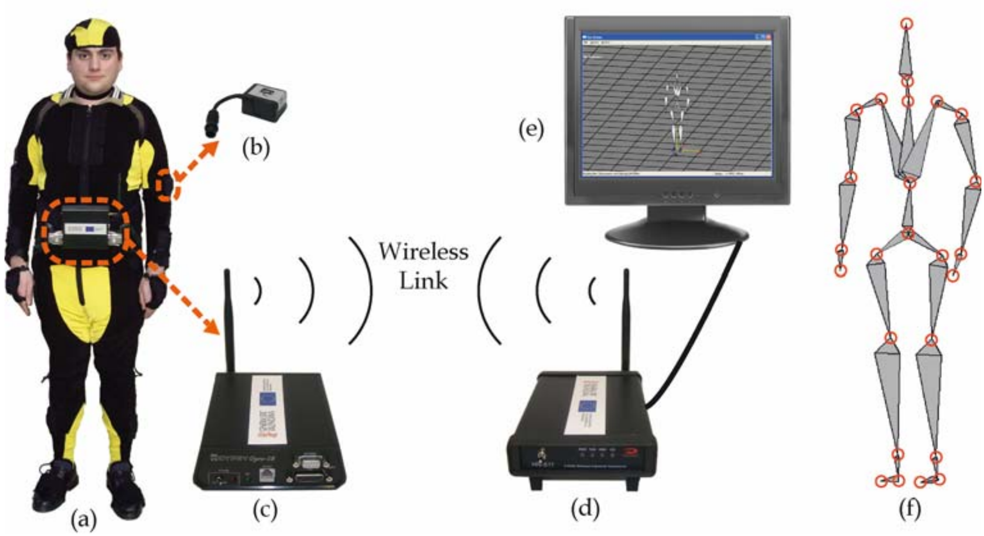


Fig. 1. Components of the inertial motion capture system: (a) suit, (b) IMU, (c) MPU, (d) wireless modem, (e) controller PC and (f) skeleton structure.

(Foxlin *et al.*, 1998). All the IMUs are connected to a MPU (Main Processing Unit, Fig. 1c) which recovers orientation measurements and sends them wirelessly to a controller PC (Fig. 1d and Fig. 1e). This PC calculates the global translation of the user in the environment with a software algorithm with determines the length of the user's steps. Limbs' rotations registered by the IMUs are applied over a 3D skeleton (Fig. 1f) which represents the basic structure of the human operator.

Orientation measurements returned by these IMUs have a resolution of 0.1º and an accuracy of 1º in yaw and 0.25º in roll and pitch. These rotational errors are small enough for most industrial applications. Nevertheless, the accuracy of the global translation measurements estimated by the footstep extrapolation algorithm is not specified by the manufacturer. A set of experiments has been developed in order to quantify the translational error of the system. In these experiments, a person who is wearing the motion capture suit walks along a linear path of different lengths (200, 300 and 400cm). The error values obtained by comparing translation measurements from the motion capture system and actual distances of the experiments are shown in Table 1. These errors are very high for industrial purposes and an additional localization system is needed in order to correct them. The following section describes the UWB location system which has been used in this chapter.

Distance (cm)	Minimum error	Maximum error	Mean error	Standard Deviation
200	16.70	66.04	40.10	17.92
300	15.33	69.54	37.92	20.97
400	35.43	64.23	51.09	10.67

Table 1. Global translation error statistics (in cm) in the motion capture system.

2.2 UWB location system

A location system based on UWB pulses has been used because it has some advantages over other wireless indoor location systems (Liu et al., 2007). The small temporal duration of UWB pulses makes them less susceptible to multipath fading and interferences than other radio-frequency technologies. In addition, the infrastructure that has to be installed in the workspace is smaller than other technologies (e.g. ultrasound) because sensors have a bigger operating range.

The UWB system used in this chapter (Ubisense, 2008) consists of two kinds of hardware devices: sensors (Fig. 2a and Fig. 2b) and tags (Fig. 2c). Sensors are situated at fixed positions in the localization area. Tags are small devices, of similar size to a credit card, which are carried by the user. The tag sends UWB pulses to the sensors, which use a combination of TDOA (Time-Difference of Arrival) and AOA (Angle of Arrival) techniques to estimate the 3D location of the user who is carrying the tag (Ubisense, 2007).

The UWB sensors are connected to an Ethernet switch (Fig. 2d) and send the location information to a controller PC (Fig. 2e) which estimates the global position of the tag in the coordinate system of the UWB system. Slave sensors are also connected to a master sensor for synchronization in the TDOA algorithm.

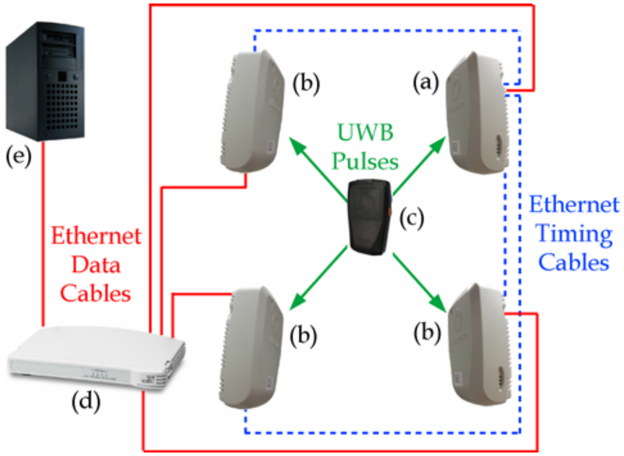


Fig. 2. Components of the UWB location system: (a) master sensor, (b) slave sensors, (c) tag, (d) Ethernet switch and (e) controller PC.

3. Sensor fusion algorithms

The experiments described in Table 1 have shown that translational measurements from the motion capture system have high error values (larger than 60cm in many cases). The UWB localization system obtains more accurate position measurements with errors smaller than 15cm. Nevertheless, the sampling rate of the UWB system (5-9Hz) is not high enough to track quick human movements in industrial environments. On the other hand, the inertial motion capture system supplies high data rates (30-120Hz).

Since both tracking systems have complementary features, their combination will make the most of their advantages. UWB measurements will be used to correct the accumulated drift in the position estimated by the motion capture system. Position measurements from the motion capture system which are obtained between each pair of UWB measurements will be used to reduce the latency of the UWB system. Thereby, the resulting system from the fusion of both trackers will have a higher sampling rate and a better accuracy than each system separately. Rotational measurements for each joint (obtained directly from the IMUs) will remain unchanged because they are accurate relative rotation transformations in the skeleton structure of the motion capture system.

In the following sections, two algorithms for combining the measurements of both tracking systems are explained in detail. The first algorithm is a simple approach where the measurements of both systems are transformed to the same coordinate system and each UWB measurement is used to correct the following motion capture measurements. The second algorithm is based on a Kalman filter which has been modified in order to incorporate the measurements of the two tracking systems.

3.1 Transformation recalculation algorithm

The first step to combine global position measurements of both tracking systems is to represent them in the same coordinate system. The frame *U* of the UWB system is a fixed coordinate system in the workspace because it is established according to the static positions

where the UWB sensors are installed. However, the frame I of the inertial motion capture system is a dynamic coordinate system because it is established in the place where the user is standing every time the system is initialized. The frame U of the UWB system has been selected as the reference coordinate system because it is able to compare the position of the human operator with the position of static objects (like machinery) in the environment.
XY planes of the U and I frames are parallel to the plane of the floor in the environment. Therefore, between the motion capture frame and the UWB frame there is only a translation and a rotation about the Z axis. Equation (1) is used to transform a point p from frame I to frame U:

$$p^U = {}^U T_I \cdot p^{\,I} = Trans\left(t_x, t_y, t_z\right) \cdot Rot\left(z^U, \alpha\right) \cdot p^I \tag{1}$$

The development of equation (1) results in the following equation:

$$\begin{bmatrix} x^U \\ y^U \\ z^U \\ 1 \end{bmatrix} = \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) & 0 & t_x \\ \sin(\alpha) & \cos(\alpha) & 0 & t_y \\ 0 & 0 & 1 & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x^I \\ y^I \\ z^I \\ 1 \end{bmatrix} \tag{2}$$

The parameter α is a known constant value which represents the angle between the Y axis of the frames U and I. Therefore, the only unknown of the transformation matrix ${}^U T_I$ are the three coordinates of the translation vector between frame U and frame I. They can be calculated from equation (2) by substituting two corresponding measurements of both systems:

$$t_x = x^U - x^I \cos(\alpha) + y^I \sin(\alpha) \tag{3}$$

$$t_y = y^U - x^I \sin(\alpha) - y^I \cos(\alpha) \tag{4}$$

$$t_z = z^U - z^I \tag{5}$$

After obtaining the transformation matrix ${}^U T_I$, all the translational measurements from the motion capture system will be transformed to the UWB frame by applying equation (1).
However, if the transformation matrix ${}^U T_I$ is calculated only when the system is initialized (with the first two measurements), the motion capture system will accumulate translational errors through time. The measurements from the UWB system have to be used in order to correct these errors. Therefore, this transformation matrix is estimated each time a new UWB measurement is received (p^U_{uwb}). The following measurements from the inertial motion capture system ($p_{inertial}$) are transformed from the I frame ($p^I_{inertial}$) to the U frame ($p^U_{inertial}$) by applying this new transformation matrix. These transformed measurements are used as estimates of the global position of the operator in the environment. The transformation recalculation corrects the accumulated translation errors from the motion capture system while the high rate of its measurements is maintained. The complete fusion algorithm is summarized in Fig. 3.

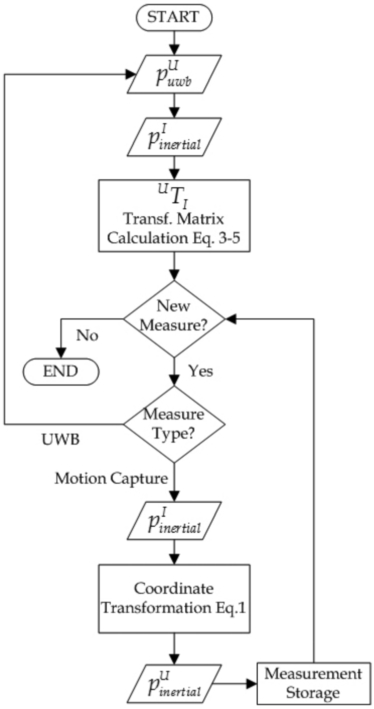


Fig. 3. Diagram of the transformation recalculation fusion algorithm.

3.2 Kalman filter algorithm

3.2.1 Previous work on Kalman filtering sensor fusion

Pose (position and orientation) estimation by inertial sensors is a well-studied field with applications in: vehicle navigation, virtual reality (VR), augmented reality (AR), robotics and human motion capture. Positions and orientations are calculated by integrating accelerations and angular rates respectively returned by accelerometers and gyroscopes. This dead reckoning process introduces a small error (drift) which is accumulated through time and becomes considerable in a few seconds. Location systems based on inertial sensors usually include additional sensors (e.g. GPS, ultrasound, magnetic, cameras, UWB and WiFi) which return absolute pose measurements in order to correct the inertial drift. In these hybrid location systems, Bayes filtering techniques (Fox et al., 2003) are generally used to estimate probabilistically the system's pose (state) from the noisy measurements of the sensors (observations). Kalman filters are the most commonly used technique to implement Bayesian filters. Different adaptations of the Kalman filter (Simon, 2001) have been proposed in previous work in order to combine measurements from several sensors. The two adaptations more commonly used are: the complementary Kalman filter and the definition of several channels (measurement models) in the correction step of the filter.

A complementary Kalman filter is an easy way to integrate several sensors measurements in a Kalman filter because the internal structure of the filter is not changed. Complementary Kalman filters estimate sensors errors instead of direct measurements. They receive as input the differences between the sensors measurements. (Foxlin, 1996) develops an IMU based on a complementary Kalman filter for head-tracking in virtual environments. It is composed by three orthogonal angular rate gyroscopes, a two-axis inclinometer and a two-axis compass. This system estimates errors in orientation (from the inclinometer and the compass) and angular rate (from the gyros). The complementary Kalman filter has also been used by (Foxlin, 2005) in a navigation system which tracks the location of a pedestrian from two IMUs mounted on his/her shoes and a GPS receiver. (Roetenberg et al., 2007) presents a human motion capture system which uses the differences between an inertial tracking system and a magnetic tracker in position and orientation as the measurement updates for a complementary Kalman filter.

(Caron et al., 2006) extends the definition of the Kalman filter to include measurements from multiple sensors (an IMU and a GPS receiver) in the correction step. This Kalman filter has one measurement model for each sensor type which is weighted according to fuzzy context variables. These fuzzy variables represent sensors data reliability and are used to reject bad measurements. (You & Neumann, 2001) develops a similar solution where an extended Kalman filter with two independent correction channels combines position measurements from a camera and orientation measurements from three orthogonal rate gyroscopes.

3.2.2 Description of the proposed algorithm

The generic Kalman filter algorithm (Simon, 2001) has been adapted to incorporate sensor measurements from the two tracking systems. The state of the Kalman filter is modelled by two parameters at each step *t*: the state estimate $\hat{p}_t$ and the error covariance matrix P_t. The state p_t is composed by the coordinates $p_t = (x_t, y_t, z_t)$ of the global position of the human operator in the environment. These two parameters are calculated by the Kalman filter in two steps: prediction and correction. The prediction step uses a state evolution model where the a-priori estimate of the state $\hat{p}_t^-$ is obtained from the current measurement of the inertial motion capture system $p_{inertial}^t$ plus a Gaussian noise $w_{inertial}^t$:

$$\hat{p}_t^- = p_{inertial}^t + w_{inertial}^t \tag{6}$$

This model is implemented in the Kalman filter prediction step using the following two equations:

$$\hat{p}_t^- = Ap_{inertial}^t \tag{7}$$

$$P_t^- = AP_{t-1}A^T + Q \tag{8}$$

The matrix A represents the state transition model of (6) and thus it is a 3x3 identity matrix which uses the last measurement from the motion capture system as the current state estimate. In the correction step, measurements from the UWB system p_{uwb}^t are modelled from the last state estimate of the prediction step $\hat{p}_t^-$ plus a Gaussian noise w_{uwb}^t:

$$p_{uwb}^t = \hat{p}_t^- + w_{uwb}^t \tag{9}$$

This measurement model is implemented in the Kalman filter correction step using the following three equations:

$$K_t = P_t^- H^T \left(H P_t^- H^T + R \right)^{-1} \tag{10}$$

$$\hat{p}_t = \hat{p}_t^- + K_t \left(p_{uwb}^t - H \hat{p}_t^- \right) \tag{11}$$

$$P_t = \left(I - K_t H \right) P_t^- \tag{12}$$

Position measurements from the UWB system are used as observations p_{uwb}^t in this step in order to correct the predicted position $\hat{p}_t^-$ calculated from the motion capture system. The matrix H represents the measurement model of (9) and it is a 3x3 identity matrix because UWB measurements have the same dimension as the state.

Error covariance matrices (Q and R) of the Kalman filter are 3x3 diagonal matrices because error components are not correlated. The diagonal terms of both matrices represent the variance of error of each tracking system (motion capture and UWB, respectively) and have been adjusted experimentally in order to reduce the errors in the final state estimates.

The implemented algorithm is depicted in Fig. 4. The prediction step (equations (7) and (8)) is executed when a measurement from the inertial motion capture system is received while the correction step (equations (10), (11) and (12)) is executed when UWB measurements are received. The main advantage of this algorithm over previous sensor fusion techniques

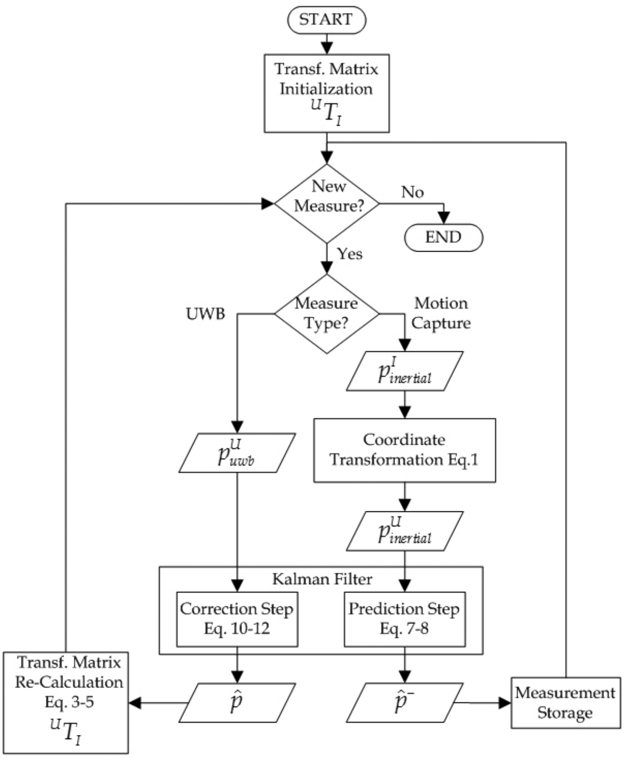


Fig. 4. Diagram of the Kalman filter fusion algorithm.

based on Kalman filtering (see section 3.2.1) is that only one step of the algorithm (prediction or correction) is executed each time a measurement is obtained. Thereby, the execution time of the algorithm is smaller. In addition, the prediction step of the developed algorithm adjusts better to changes in the movements of the operator because it uses real position measurements from the inertial motion capture system. Previous Kalman filter algorithms implement theoretical kinematic models which suppose that the velocity (You & Neumann, 2001) or the acceleration (Caron et al., 2006; Roetenberg et al., 2007) of the operator can be represented as a constant value plus a Gaussian noise.

Although this approach implies executing the correction step with a lower rate than the prediction step, this fact does not imply a dramatic reduction in the accuracy of the estimated states. The error accumulated by the motion capture system between each pair of UWB measurements is not significant and it is not accumulated for future motion capture measurements after a new UWB measurement is received. This is because the corrected state estimate obtained from the last UWB measurement is used to recalculate the transformation matrix ${}^{U}T_{I}$ between the frames of both tracking systems. This new transformation matrix is applied to the subsequent measurements from the motion capture system and thus the error of the previous measurements is removed.

4. Experimental results

4.1 Comparison between the fusion algorithms

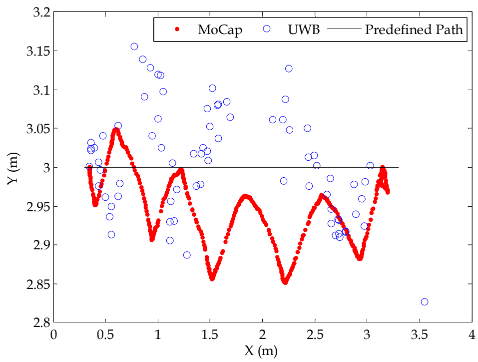
Some experiments have been performed to compare the accuracy of the two fusion algorithms presented in the previous sections. A human operator wearing the motion capture suit and a UWB tag has walked along two different pre-established paths: a linear trajectory (3m) and a rectangular trajectory (8m). Each trajectory has been repeated fifteen times. These measurements are processed in two Matlab functions which implement the two fusion algorithms.

In Fig. 5a, original measurements from the UWB system and the motion capture (MoCap) system in an experiment of the linear trajectory are represented in the same coordinate system. This plot shows the advantages and disadvantages of both tracking systems. On one hand, motion capture measurements have a higher sampling rate but they accumulate an error which increases through time. On the other hand, UWB measurements have a smaller sampling rate but do not accumulate errors through time.

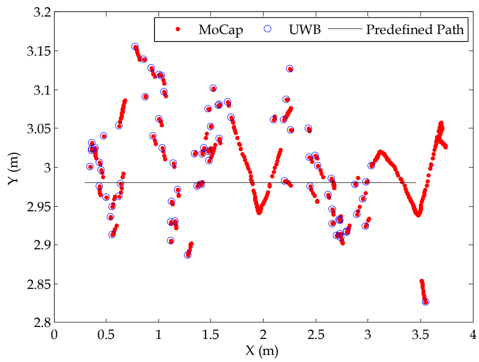
Fig. 5b and Fig. 5c depict the position estimates obtained from the fusion algorithms. The trajectories obtained by the Kalman filter algorithm (Fig. 5c) are more continuous than the trajectories from the transformation recalculation algorithm (Fig. 5b). In addition, the position estimates of the Kalman filter have smaller errors than those of the transformation recalculation algorithm (Fig. 5d).

In Fig. 6a, Fig. 6b and Fig. 6c, an experiment of the rectangular trajectory is represented and similar results are obtained. The estimates obtained from the Kalman filter are more precise than those from the transformation recalculation algorithm (Fig. 6d). The higher accuracy of the Kalman filter estimates is due to the fact that this algorithm takes into account the errors of both tracking systems while the transformation recalculation algorithm only corrects the errors of the motion capture system. The transformation recalculation algorithm uses the

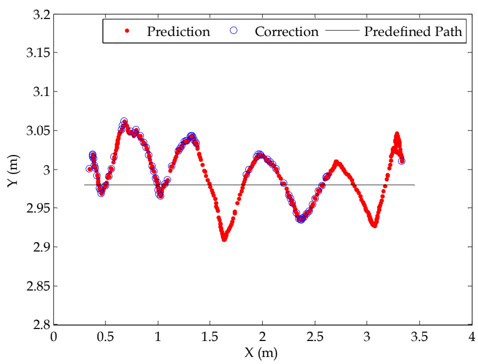
UWB measurements as correct positions in order to calculate the transformation matrix and thus correct the motion capture errors. However, the errors of the UWB system are not corrected and cause discontinuities in the trajectories (Fig. 5b and Fig. 6b). In conclusion, the Kalman filter fusion algorithm obtains more accurate position estimates and continuous trajectories and it will be used to implement human-robot interaction tasks where the human operator has to be localized precisely.



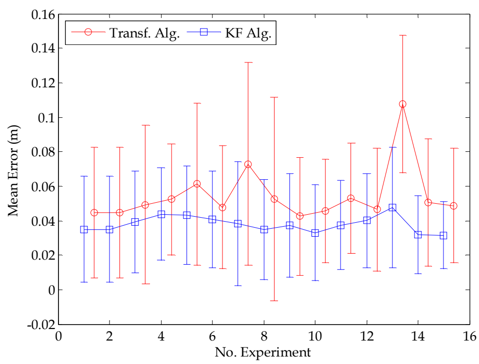
(a)



(b)



(c)



(d)

Fig. 5. Linear trajectory experiments: (a) original position measurements from both tracking systems in experiment no. 14; (b) position measurements obtained from the transformation recalculation algorithm in experiment no. 14; (c) position estimates obtained from the prediction and correction steps of the Kalman filter algorithm in experiment no. 14; (d) mean error and standard deviation of the position estimates from the two fusion algorithms in the 15 linear path experiments.

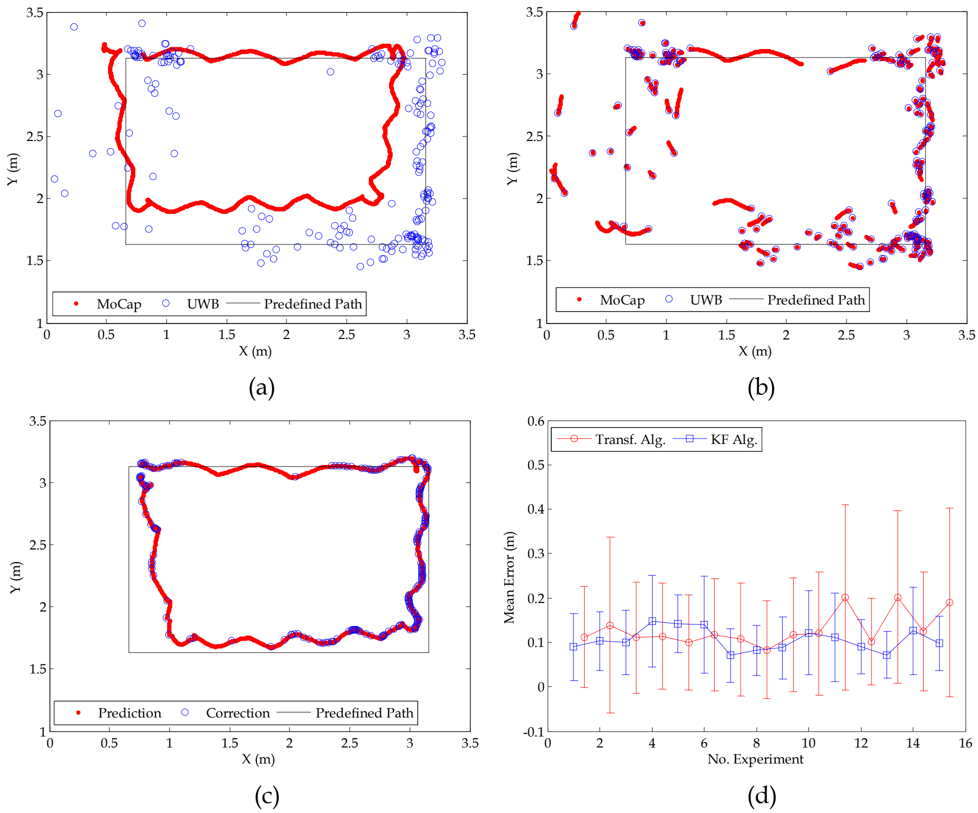
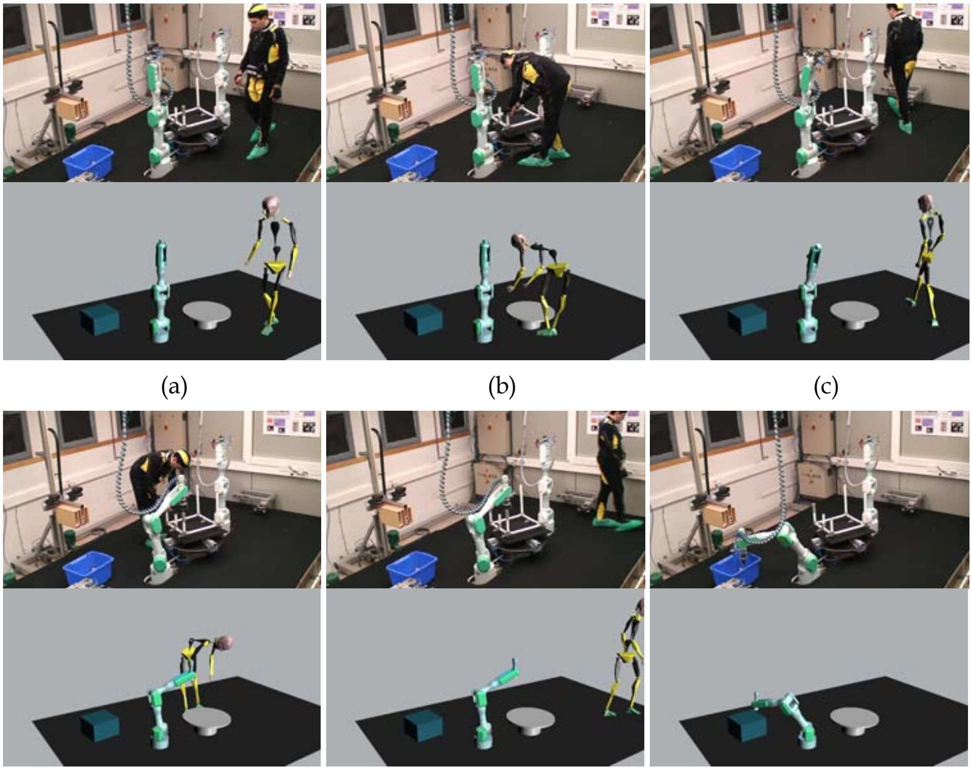


Fig. 6. Rectangular trajectory experiments: (a) original position measurements from both tracking systems in experiment no. 3; (b) position measurements obtained from the transformation recalculation algorithm in experiment no. 3; (c) position estimates obtained from the prediction and correction steps of the Kalman filter algorithm in experiment no. 3; (d) mean error and standard deviation of the position estimates from the two fusion algorithms in the 15 rectangular path experiments.

4.2 Application in a human-robot interaction task

The global position measurements obtained from the Kalman filter fusion algorithm and the joint rotations registered by the motion capture system are applied to the skeleton model of the human operator in order to perform human-robot interaction tasks. In Fig. 7, a collaboration task between a robotic manipulator (Mitsubishi PA-10) and a human operator is shown. The main frames of the task are depicted with the corresponding models of the human operator and the robot. In this task, the robotic manipulator has to remove two connectors from a metallic structure in order to leave them in a storage box. However, the collaboration of a human operator is needed because the unscrewing of the connectors is a difficult action to be performed by one robot.

Firstly, the operator unscrews the first connector (Fig. 7a and Fig. 7b). When the operator has finished the unscrewing process, the robotic manipulator begins to move towards the structure by using a time-independent visual sevoing technique (Garcia et al., 2007) in order to grab the unscrewed connector (Fig. 7c). The end of the unscrewing process is determined by the tracking of the human operator. In particular, the robot does not begin its task until the distance between the end-effector of the robot and the operator is greater than a safety threshold (1m). While the robot is removing the first connector from the structure, the human operator unscrews the other connector (Fig. 7d). When the human operator has finished unscrewing the second connector, he leaves the robotic workspace (Fig. 7e). Finally, the manipulator places the first connector inside the storage box (Fig. 7f). The removing of the second connector has not been depicted in Fig.7 for the sake of clarity but it is very similar to the processing of the first connector.



(a) (b) (c) (d) (e) (f)

Fig. 7. Sequence of 6 frames of a human-robot interaction task. The skeleton of the human obtained from the tracking systems by using the presented Kalman filter algorithm and the model of the robot are depicted below each frame.

5. Conclusions

In this chapter, two different algorithms have been developed to combine position measurements from two human tracking systems: an inertial motion capture system and a UWB location system. The first algorithm recalculates the transformation matrix between the coordinate systems of both trackers each time a UWB measurement is received. The error accumulated by the inertial motion capture system is therefore removed because the following measurements are transformed to the UWB frame with this new transformation matrix. However, this approach considers the UWB measurements as completely correct data and ignores their errors. The errors of the UWB system are not corrected and they are transferred to the measurements obtained from the fusion algorithm.

The second fusion algorithm is based on a Kalman filter and solves the drawbacks of the first algorithm. The Kalman filter algorithm models the errors of both tracking systems and takes them into account to estimate the position of the human operator. Several experiments have been developed to verify that this algorithm based on a Kalman filter obtains more accurate position estimates and more continuous trajectories than the first algorithm. In this algorithm, the prediction step of the Kalman filter is executed when measurements from the inertial motion capture system are received and the correction step is only executed when measurements from the UWB system are obtained. Thereby, this Kalman filter algorithm has a better computational cost than previous Kalman filter fusion algorithms which complete both steps of the filter (prediction and correction) each time a new measurement is received.

Finally, the position estimates obtained from the Kalman filter algorithm and the rotations from the motion capture system have been applied to a human skeleton model in order to develop a real collaborative task between a human operator and a robotic manipulator. In this task, the real-time tracking of the human operator does not only guarantee the safety of the operator but also determines the behaviour of the robot. Thus, the robot does not start its trajectory until the human has finished the previous task and is at a safety distance from the robot.

In future work, the movements of the skeleton should be interpreted in order to understand behaviours of the human operator and thus develop more complex collaboration tasks between robots and humans.

6. Acknowledgments

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